AN IMPROVED DATA CLASSIFICATION FRAMEWORK BASED ON FRACTIONAL PARTICLE SWARM OPTIMIZATION

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Dedicated to my beloved parents, grandparents, siblings, friends and lecturers, without your support, guidance and encouragement, I might not have had this kind of achievement. Thanks for all the support, guidance and patience during my PhD journey.

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ABSTRACT

Particle Swarm Optimization (PSO) is a population based stochastic optimization technique which consist of particles that move collectively in iterations to search for the most optimum solutions. However, conventional PSO is prone to lack of convergence and even stagnation in complex high dimensional-search problems with multiple local optima. Therefore, this research proposed an improved Mutually-Optimized Fractional PSO (MOFPSO) algorithm based on fractional derivatives and small step lengths to ensure convergence to global optima by supplying a fine balance between exploration and exploitation. The proposed algorithm is tested and verified for optimization performance comparison on ten benchmark functions against six existing established algorithms in terms of Mean of Error and Standard Deviation values. The proposed MOFPSO algorithm demonstrated lowest Mean of Error values during the optimization on all benchmark functions through all 30 runs (Ackley = 0.2, Rosenbrock = 0.2, Bohachevsky = 9.36E-06, Easom = -0.95, Griewank = 0.01, Rastrigin = 2.5E-03, Schaffer = 1.31E-06, Schwefel 1.2 = 3.2E-05, Sphere = 8.36E-03, Step = 0). Furthermore, the proposed MOFPSO algorithm is hybridized with Back-Propagation (BP), Elman Recurrent Neural Networks (RNN) and Levenberg-Marquardt (LM) Artificial Neural Networks (ANNs) to propose an enhanced data classification framework, especially for data classification applications. The proposed classification framework is then evaluated for classification accuracy, computational time and Mean Squared Error on five benchmark datasets against seven existing techniques. It can be concluded from the simulation results that the proposed MOFPSO-ERNN classification algorithm demonstrated good classification performance in terms of classification accuracy (Breast Cancer = 99.01%, EEG = 99.99%, PIMA Indian Diabetes = 99.37%, Iris = 99.6%, Thyroid = 99.88%) as compared to the existing hybrid classification techniques. Hence, the proposed technique can be employed to improve the overall classification accuracy and reduce the computational time in data classification applications.

ABSTRAK

Pengoptimuman Swarm Partikel (PSO) adalah teknik pengoptimuman stokastik berasaskan populasi yang terdiri daripada zarah-zarah yang bergerak secara kolektif dalam lelaran untuk mencari penyelesaian yang paling optimum. Walaubagaimanapun, PSO yang konvensional terdedah kepada kekurangan penumpuan dan juga genangan dalam masalah carian dimensi tinggi kompleks dengan pelbagai optima tempatan. Oleh itu, kajian ini mencadangkan algoritma Fractional PSO (MOFPSO) yang dipertingkatkan secara mutlak berdasarkan pembezaan pecahan dan jarak langkah kecil untuk memastikan penumpuan kepada optima global dengan menyediakan keseimbangan yang baik antara eksplorasi dan eksploitasi. Algoritma yang dicadangkan diuji dan disahkan untuk perbandingan prestasi pengoptimuman pada sepuluh fungsi penanda aras berbanding enam algoritma yang sedia ada yang wujud dari segi Purata Ralat dan nilai sisihan piawai. Algoritma MOFPSO yang dicadangkan menunjukkan nilai Purata Ralat terendah semasa pengoptimuman pada semua fungsi penanda aras melalui semua 30 ulangan (Ackley = 0.2, Rosenbrock = 0.2, Bohachevsky = 9.36E-06, Easom = -0.95, Griewank = 0.01, Rastrigin = 2.5E -03, Schaffer = 1.31E-06, Schwefel 1.2 = 3.2E-05, Sphere = 8.36E-03, Step = 0). Tambahan lagi, algoritma yang dicadangkan itu hibridisasi dengan Propagasi-Pembalikan (BP), Rangkaian Neural Ulangan Elman (RNN) dan Levenberg-Marquardt (LM) Rangkaian Neural Buatan untuk mencadangkan rangka kerja klasifikasi data yang dipertingkatkan, terutamanya untuk aplikasi klasifikasi data. Rangka klasifikasi yang dicadangkan kemudiannya dinilai untuk ketepatan klasifikasi, masa pengiraan dan Ralat Purata Kuadrat pada lima dataset penanda aras terhadap tujuh teknik yang sedia ada. Ia dapat disimpulkan dari hasil simulasi bahawa algoritma MOFPSO-ERNN yang dicadangkan menunjukkan prestasi klasifikasi yang unggul berbanding dengan algoritma deterministik yang sedia ada (Kanser Payudara = 99.01%, EEG = 99.99%, Diabetes PIMA India = 99.37%, Iris = 99.6% Thyroid = 99.88%). Oleh itu, teknik yang dicadangkan boleh digunakan untuk meningkatkan ketepatan klasifikasi keseluruhan dan mengurangkan masa pengiraan dalam aplikasi klasifikasi data.

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LIST OF SYMBOLS AND ABBREVIATIONS

i	-	Subscript i correspond to input nodes
j	-	Subscript j correspond to hidden nodes
k	-	Subscript k correspond to output nodes
w_{jk}	-	Weight from node j to node k
w_{ij}	-	Weight from node i to node j
v_i^{t+1}	-	Velocity vector for Each Particle
x_i^t	-	Position vector for Each Particle
α	-	Acceleration Constant in PSO
α_f	-	Alpha value in MOFPSO
ε_n	-	Random vector drawn from N (0, 1)
e	-	Exponential
σ^2	-	Measure of Variance
σ	-	Standard Deviation
x	-	Variable with Normal Distribution
μ	-	Mean Value
$\otimes$	-	Hadamard Matrix Product Operator for Step-wise Multiplication
T_i	-	i^{th} Target output
Y_i	-	i^{th} Network output
δ_k	-	k^{th} Node error of output layer
δ_j	-	j^{th} Node error of hidden layer
h_j	-	j^{th} Output of the hidden node
O_i	-	i^{th} Output of the input node
η	-	Rate of learning
x^*	-	Global best solution
x^{new}	-	New local best

x^{old}	-	Previous local best
A_i	-	Actual data
v	-	Velocity of Each Particle
n	-	Total number of particles
x^{max}	-	Maximum data range
x^{min}	-	Minimum data range
U	-	Upper normalization boundary
L	-	Lower normalization boundary
T_i	-	Predicted data
Xi	-	The observed value
$\bar{X}_i$	-	Mean observed value
NNs	-	Neural Networks
ABC	-	Artificial Bee Colony Algorithm
ABC-BP	-	Artificial Bee Colony Algorithm with Back Propagation
ABC-LM	-	Artificial Bee Colony Algorithm with Levenberg-Marquardt
AUROC	-	Area under the Receiver Operating Characteristic
BP/BPNN	-	Back Propagation Neural Network
CS	-	Cuckoo Search
ERN/ERNN	-	Elman Recurrent Neural Network
GA	-	Genetic Algorithm
GA-BP	-	Genetic Algorithm with back propagation
GA-LM	-	Genetic Algorithm with Levenberg-Marquardt
HS	-	Harmony Search
IANN	-	Improved Artificial Neural Networks
LM	-	Levenberg-Marquardt
MSE	-	Mean Squared Error
PSO	-	Particle Swarm Optimization
RNN	-	Recurrent Neural Network
ROC	-	Receiver Operating Characteristics
WSA	-	Wolf Search Algorithm

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Fundamentally, the word classification regarding daily life refers to selecting or deciding a future conduct based on the presently available information such as categorization of foods, allocation of salaries based on the work load and sorting of daily mail based on post codes (Brunelli, 2009). A more formal and modern definition of machine-based classification provided by Tom Mitchell, a very well-known computer scientist, is that, "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."

Machine-based classification usually involves some computer programs, known as algorithms, developed using several mathematical formulations to accelerate the automated classification process. With increase in the size and computational complexity of the data today, such optimized, robust, agile and reliable computational algorithms are required which can efficiently carry out these conforming classification tasks. In this regard, Machine Learning (ML) techniques have been demonstrated to be excellent tools to deal with these complex problems regularly arising from various sources (Kotsiantis, 2007). It is one of today's most rapidly growing technical fields, lying at the intersection of computer science and statistics and at the core of artificial intelligence and data science (Pérez-Ortiz *et al.*, 2016). There are several applications of ML, the most significant of which is data mining (Buczak & Guven, 2016). People are often prone to making mistakes during analyses or, possibly, when trying to establish relationships between multiple features in a dataset. This makes it difficult for them to find solutions to certain problems, especially, if the addressed problem is large in volume. ML can provide effective solutions to these problems, by improving the efficiency of optimization and classification systems.

Apple and Orange classification is a typical example to understand the concept of classification as shown in Figure 1.1. Manual classification can be easily performed on a small scale if the task is to separate the two fruits from each other.

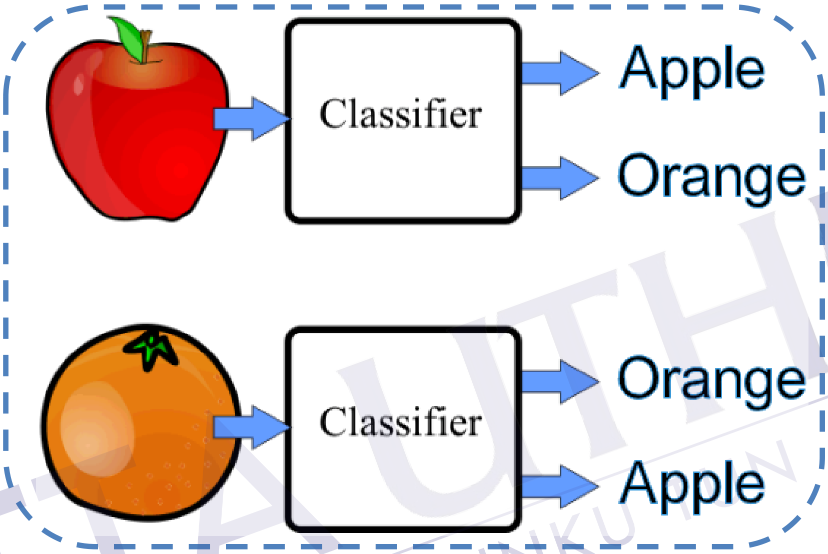

Figure 1.1: Typical example of a classification process

Whereas, in an industrial environment, where there is large amount of the fruits to be separated from each other on a conveyer belt is a tedious and time taking job. This is where automated ML based classification comes in to play to classify and separate the fruits from each other. This type of classification is known as binary classification, where there are a specific number of known input attributes and a specific number of known output classes. For example, in the above-mentioned example, the fruits can be classified based on color i.e. Red color represents Apples and Orange color represents Oranges.

In machine learning algorithms, every instance in any dataset is represented using the same set of continuous, categorical or binary features (Kotsiantis, 2007). Table 1.1 shows a basic concept of data classification based on a specific number of inputs called features and specific corresponding required outputs known as Target classes.

Table 1.1: Basic concept of data classification

Classification Data					
Instances	Feature 1	Feature 2	…….	Feature n	Target Classes
Case 1	xxx	xx		x	Malignant
Case 2	xxx	xx		x	Benign
Case 3	xxx	xx		x	Benign
…..	…	…	…	…	…

Generally, almost all machine learning based classification problems can be assigned to one of the two major classification techniques: Supervised learning and Unsupervised learning. In supervised learning, the classifier is given a dataset and it is already aware of the desired output, having a feedback relationship between the input and the output. In a supervised classification problem, it is aimed to predict the results in a discrete output. In other words, the target is to map the input variables into distinct classes. While, unsupervised learning refers to tackle the problems with minute or no idea of the corresponding outputs. Only information available in unsupervised learning is the relationships among variables derived through clustering the likewise variables and vice versa. Where, there is no feedback based on the prediction results in unsupervised learning.

1.2 Project Background

Data classification is the most important type of data mining technique which deals with the classification of large, computationally complex datasets (Pires *et al*., 2014). Classification of these huge datasets normally takes long computational times and is also prone to less classification accuracy (Sanz *et al*., 2015). Existing classification techniques have been proved to be less efficient when implied to perform classification in high-dimensional datasets (Triguero *et al*., 2015). Lately, several hybridized classification techniques have been reported that include a combination of classification as well as optimization algorithms (Bazi *et al*., 2014). These hybridized techniques are commonly used to optimize and benefit the classification process (Devos *et al*., 2014). Bio-inspired metaheuristic optimization algorithms are most commonly employed for such hybridized techniques because of their versatile exploration and exploitation capabilities (Zhang *et al.*, 2015).

Biologically inspired, or short Bio-inspired metaheuristic algorithms are one of the most common inherited techniques that are applied in today's machine learning optimization (Wang *et al.*, 2015). This field of study is basically a combination of several subfields related to the topics of social behavior of living organisms and computing systems (Seera & Lim, 2014). It suggests ways to implement characteristics and components of artificial intelligence in machine learning optimization (Ren *et al.*, 2016). Fundamentally, it depends on the fields of biology, computer science and mathematics to model the social and cognitive behavior of living organisms to improve machine learning optimization (Saez *et al.*, 2015). Such bio-inspired machine learning algorithms that tend to mimic the collective social and cognitive characteristics of living organisms in groups such as flocks of birds or school of fish are referred to as swarm intelligent algorithms (Masethe & Masethe, 2014).

The term '*Swarm Intelligence*' was coined in 1989 by Gerardo Beni and Jing Wang (Beni and Wang, 1989). Subsequently, swarm intelligence has developed as the basis of numerous bio-inspired metaheuristic search algorithms (Radwan & Fouda, 2013; Krawczyk *et al.*, 2014). *Meta* means 'to look beyond' or 'higher level' and *heuristic* means 'to search' or 'to discover by trial and error' (Sanz *et al.*, 2014). Briefly put, swarm intelligent metaheuristics can be defined as high-level approaches for exploring search spaces by using different methods (Blum *et al.*, 2008).

Swarm based metaheuristic optimization methods are also known as stochastic optimization techniques which aim to randomly explore the search space to find the most optimum solution (Kingma & Ba, 2014; Gilli & Winker, 2008). It is maintained that stochastic optimization techniques can produce high quality approximation of the global optimum as compared to deterministic, less optimal local minima provided by conventional techniques (Yang, 2018). Stochastic optimization algorithms iterate to optimize a problem by attempting to improve the candidate solution according to a given measure of quality defined by the respective fitness function (Li *et al.*, 2014).

Some current examples of metaheuristics are Particle Swarm Optimization (PSO) which has been successfully applied in many engineering applications (Robinson & Rahmat-Samii, 2004; Jin & Rahmat-Samii, 2007).

Ant Colony Optimization (ACO) algorithm has also been used in many areas of optimization (Merkle *et al.*, 2002; Parpinelli & Lopes, 2011).

Artificial Bee Colony (ABC) algorithm demonstrated good performance in numerical optimization (Karaboga & Basturk, 2007; Karaboga & Basturk, 2008), in large-scale global optimization (Fister & Zumer, 2012), and also in combinatorial optimization (Neri & Tirronen, 2009; Pan *et al*., 2011; Parpinelli & Lopes, 2011). Recently, a new set of metaheuristics are added to the family of age long swarm intelligent algorithms.

These bio-inspired optimization algorithms include Firefly (Zheng *et al*., 2015; Yang, 2009), Cuckoo Search (Yang & Deb, 2009), Wolf Search (Tang *et al.*, 2012) and Bat algorithm (Yang, 2010a). These metaheuristic optimization algorithms follow multi-dimensional search methods that are heavily inspired from the movement patterns and social and cognitive behavior of swarm of animals and insects found in the nature (Uryasey & Pardalos, 2013; Arsenault *et al.*, 2013). The performance of such swarm-based metaheuristic optimization algorithms has been demonstrated to be better in comparison to the existing conventional methods (Homem-de-Mello & Bayraksan, 2014). There are two main components of any metaheuristic search-based algorithm i.e. exploration and exploitation (Liu *et al*., 2016).

Exploration in metaheuristic algorithms is accomplished using randomization to search much larger search space in the quest of finding more promising solutions (Donadee & Ilić, 2014). Exploration process is responsible for diversification, which helps an algorithm to search globally and avoid local optima (Schkufza *et al*., 2014; Munos, 2014). While, exploitation process offers intensification in which new neighborhood solutions are navigated locally to find a better solution than the already found optimal one (Neri & Tirronen, 2009; Yang *et al*., 2014).

1.3 Problem Statement

Data classification is the most important type of data mining technique which deals with the classification of large, computationally complex datasets. Classification of these huge datasets using existing techniques lead to higher computational times and decreased accuracy. Recently, several hybridized classification algorithms based on optimization techniques are proposed and commonly used to optimize and benefit the classification process (Manjarres *et al.*, 2013; Cheng & Prayogo, 2014; Zhang *et al.*, 2015; Ervural *et al.*, 2017). Bio-inspired metaheuristic algorithms are most commonly used for such hybridized techniques because of their versatile exploration and exploitation capabilities (Yang *et al.*, 2013).

PSO is one of the most extensively employed evolutionary algorithms for such optimization problems. Nevertheless, traditional PSO suffers from several issues when employed in complex high-dimensional problems. These issues include convergence to sub-optimal solutions and stagnation in problems with multiple local optima (Ghamisi *et al.*, 2014; Couceiro & Sivasundaram, 2016). Also, PSO algorithm uses longer step lengths which can cause it to skip optimal solutions in the space (Zhang *et al.*, 2015). Furthermore, in PSO, there exists a trade-off between exploration and exploitation, where, favouring either will end up low quality outcomes due to negligence of the other (Tam *et al.*, 2018). These problems in PSO algorithm further add to the issues of increased computational cost and reduced accuracy in hybridized data classification techniques.

These prevailing issues in machine-based hybridized classification techniques limit the potential of automated classification systems in high-dimensional classification problems. In order to perform and assist efficient classification for such datasets, it is crucial to develop such classification techniques that can significantly reduce the computational times and improve the classification accuracy for such applications. Hence, to reduce the computational times in hybridized classification techniques using PSO and improve the overall classification accuracy, it is inevitable to improve the optimization capability of the traditional PSO algorithm.

1.4 Aim and Objectives of Research

This research is aimed to develop an enhanced, Mutually-Optimized fractional PSO algorithm-based classification framework through provision of fine balance between exploration and exploitation search of traditional PSO by introducing fractional derivatives, consequently improving the convergence behavior of traditional PSO algorithm, reducing the overall computational time and improving the classification accuracy in data classification applications.

To achieve this aim, the objectives of this research are formulated as follows:

1. To develop an enhanced MOFPSO algorithm based on fractional order velocity and shorter step lengths to ensure convergence to global optima.

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